Climate Science Meets the Energy Industry: Lessons Learned

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1. Introduction

The California Energy Security ("Calenergy") project was a one-year, NOAA sponsored effort to determine the economic value of climate forecasts to the energy industry. Climate researchers at the Scripps Institution of Oceangraphy (SIO), University of Washington (UW), and Georgia Tech (GA) worked with personnel from SAIC and various energy firms to assess the value of the climate forecasts to the energy firms' operation and planning activities. Since it was a relatively brief project, only a few (4) case studies could be selected for detailed analysis. The climate science aspects of the case studies are described elsewhere. The purpose of this note is to document some of the larger "lessons learned" when trying to have a joint project between academic climate research and the energy industry.

Briefly, the main lessons learned were as follows.

- The single most important factor for success was having a specific, motivated, and technically able person in the energy firm who was willing to work on the project.
- There is a fundamental mismatch in time scales between energy industry expectations of what "climate forecasts" can/should address, and what time scales academic climate researches think of as appropriate to climate forecasting.
- The traditional variables most commonly forecast by academic climate research, such as seasonal mean temperature, are frequently not of interest to the energy industry. Instead, there is great interest in extreme events.
- In practice, we found few businesses that were able to use the inherently probabilistic climate information in a meaningful way in their business activities.

- There is a mismatch in timescales between the time over which climate forecasts are evaluated as being successful or not, and that over which business decisions are evaluated as being successful or not.
- The energy industry firms were generally only interested in the climate researchers generating climate forecasts, not load forecasts, even if it would be more sensible to directly predict load.

Each of these points will now be illustrated from our experiences.

2. Most important factor for success: the business participant

By far, we found that the single most important factor that separated successful case studies from less than successful ones was the presence of a motivated, technically competent individual in the energy firm who was specifically assigned to the project. This is an important point, because before starting the project we had imagined that the paradigm for the project would be the more traditional one used in weather and climate forecasting, which might informally be summarized as "if you produce it, they will come." For example, El Nino (ENSO) forecasts are produced by various groups and disseminated by being put on a web site; anyone who wants to use them can come and get them.

In our project, we did not find any energy firms who were actually *using* this kind of climate data, despite its availability. Often they were aware of its existance but chose not to use it. Some common reasons for this were:

1. Wrong variable being forecast; i.e., seasonal mean temperature was of little interest.

2. Not enough information about reliability and applicability of the forecast, and in general its error statistics.

3. Nobody to ask about details of the forecast; in general the firms seemed to want to have an identified climate scientist to work with, rather than some faceless web site.

4. Did not understand the information conveyed, as it was couched in unfamiliar language or terms.

It was really only when we had a motivated person in the energy firm to work with that we could get these problems resolved. Perhaps the best illustration of this was with the prediction of southern California heat waves. Our case study showed it was possible, and how the company could do it themselves. However, they ultimately were not comfortable with this setup, and ended up hiring a person with a background in meteorology to do the work. Without the proper, motivated person with the appropriate background present in the company, the forecasts went unused.

Put another way, *the best way to ensure success of a climate/energy project is to make sure it is done with the specific buy-in of a motivated, technically savvy participant in the energy firm.*

3. Mismatch in time scales

If you ask an academic climate researcher what time scales are appropriate for climate forecasts, the answer is likely to be that there is skill on seasonal and on multi-decadal time scales. Seasonal skill comes from ENSO, and to a lesser extent (via persistence) via the PDO and possibly NAO, while multi-decadal skill comes from relentless anthropogenic forcing of the climate. Seasonal forecasting is basically a boundary value problem, where forecasted (or persistent) sea surface temperature or soil moisture boundary conditions bias the distribution of temperatures or rainfall. It is important to note that these biases become apparent when averaging over many independent events. The multi-decadal anthropogenic forecasting is a forced problem, where a changing distribution of gasses in the atmosphere yield predictable shifts in climate.

Short time scales, say 1 hour to 2 weeks, are basically initial value problems and considered to be the domain of weather forecasting, not climate science *per se* (although it should be noted that statistical climate techniques can be applied to such timescales, which is sometimes called statistical weather forecasting). When we interacted with people in the energy industry, we found almost inevitably that what they wanted from a "climate forecast" was *an improved 2-week to 20 day weather forecast.* This is problematical for current traditional climate forecasts, which often do not address this timescale. Whether or not it is ultimately possible to address this timescale is a matter of research at this point.

We also found demand for a 1 to a few-year climate forecast. This is the timescale on which various capital improvement projects typically proceed, for example, installing new transmission capacity or electrical substations. If such facilities could be preferentially located where they would be needed most, or if the order in which the locations to be improved could be prioritized based on the order in which the location would be likely to experience increased demand, it would be quite valuable. Unfortunately, there is little demonstrated climate forecast skill on such timescales.

We were surprised that we found so few energy industry people interested in seasonal climate forecasts. In practice, we did not make any headway in convincing energy industry participants that a skillful seasonal forecast would be valuable for their business. It may be worth noting that of the 4 case studies completed for the Calenergy project, one dealt with sub-daily timescales, two with 1 to 5 day time scales, and only one with seasonal time scales. Of course, it is entirely possible that there are many people interested in seasonal climate forecasts in the energy industry, but if our small sampling is any indication, they are a distinct minority.

We did find some planning parts of energy firms interested in the anthropogenic change issue. However, at the time of Calenergy this was substantially complicated by the politics of the issue and the disinformation campaigns regarding climate change being funded by some of the big oil companies. This is likely to change in the future.

The lesson learned here is that there might be less interest in one of climate science's premier products, seasonal climate forecasts, than a climate scientist would expect. Various solutions to this problem might be: 1) climate scientists can try to convince energy industry participants of the value of seasonal forecasts (it should be noted we didn't succeed with this in Calenergy); 2) climate scientists can choose to focus on timescales of interest to the energy industry, such as the 1-5 day timescale, although there might be little motivation for doing so if the climate researcher is not interested in "weather" *per se*; 3) there could be basic climate research into predictability on the 14-20 day time scale, which however might well take some years to be of tangible benefit to energy industry firms; 4) as more firms realize the inevitability of facing the anthropogenic climate change issue, there might be more willingness to use muti-decadal forecasts focusing on this issue.

4. Non-traditional variables needed

One issue we found repeatedly was that the traditional variables most often forecast in climate models, for example mean seasonal temperature, were of little interest to the energy industry. It was far more common to find interest in extreme threshold events, such as the number of days in a row over 95 F, and in particular in what one might call "disastrous concatenation of circumstances." For example, are we more likely to have a hot summer in California after a dry winter in the Pacific Northwest, so that there will be limited hydropower available for California air conditioners just when it is most needed?

Another aspect of this we were surprised by was the sometimes simplistic statistical models of extreme events that the energy industry uses, for example, assuming that heat waves in the Bay Area are independent of heat waves in Southern California. The inter-dependency of such events can significantly alter their chance of occurring simultaneously, and we found that often these factors were not well appreciated or correctly taken into account in systemwide demand models.

The take-home lesson from this point is that before any climate forecasts are made or even before the course of scientific research or the forecasting system is designed, *it should be understood in detail exactly what variables (and aspects of variables) are needed* and which are irrelevant to the problem. Often this will be a different choice of variables than usually assumed in climate research. Doing this successfully requires the involvement of a motivated, technically savvy person from the energy firm in question, hence the importance of such a person to the overall success of the project, as already noted above.

5. Probabilistic information not well understood

We consistently found that climate forecasts, with their inherently statistical nature, were viewed as being unusable in the businesses practices of the energy firms we worked with, which required a binary yes/no decision point.

The way energy firms treat weather forecasts gives a good illustration of this. For example, imagine that the weather forecast states that tomorrow's high will be 92 F in Sacramento. It is likely that what this actually means is that the mean expectation value for tomorrow's high temperature is 92 F, but there is some distribution about this mean value, which is usually not stated and perhaps not even obtainable. It might be that there is a 90% chance of the high being between 90 F and 94 F; or perhaps there is 90% chance of the high being between 87 F and 96 F. From the climate point of view, these two forecasts (mean 92 with 90% range of 90 to 94, and mean 92 with 90% range of 87 to 96) are different and might imply different courses of action to the energy industry. But from the viewpoint of a weather forecast as commonly disseminated, they are indistinguishable.

Because the probabilistic nature of the forecasts is hidden (or unobtainable), we found in Calenergy that business practices were not set up to take advantage of probabilistic information, and therefore inherently probabilistic climate forecasts were perceived as being unusable. This seemed to us to be mostly a matter of learning, education, and adaptation on the part of the energy industry participants – *they were using probabilistic information but were not aware of doing so and had not set up business practices to make use of all the data* – but in practice we found we could make little headway on these issues from the outside. The only times we were successful in transmitting probabilistic forecasts to the energy industry participants and having those forecasts actually used was when there was a person in the energy firm who could understand and see the value of the extra information, even though the business practices often had no formal mechanism to incorporate such information.

The lesson learned here, besides the already-emphasized one of dealing with the correct person in the energy firm, is to *provide samples of the kind of information generated by climate forecasts and see if it can actually be used* before the entire forecasting project goes ahead.

6. Climate forecast timescales vs. business decision timescales

This is in some ways a corollary of points 3 and 5 above, but since we ran into it fairly often it is worth specifically mentioning. Using a climate forecast generally represents a departure from previous business practice in an energy firm. The business decision to be made that depends on the forecast might only occur once a year, for example, when a winter forecast is issued. Because the forecast is probabilistic, there will be times when the action taken when including the climate forecast in the decision will have a *worse* outcome than if the "old" way of doing things had been used. This can lead to reluctance to use the forecast in the first place, since a year's worth of regret over a bad decision can seem to have more sway than a general trend, established over many years (perhaps decades), of being somewhat better than the old way of doing things.

Sometimes the way this was conceptualized by the energy industry participants was that they were fine with having a probabilistic forecast, but then they additionally *wanted an indication of when they should use it* (i.e., when the median forecast would be what actually occurs). For example, if a forecast indicated a 75% chance of a warmer than usual summer, we were almost inevitably asked if we could work on the problem of identifying, ahead of time, those specific 75% of years when the forecast was correct and the summer actually *would* be warmer than usual. Clearly, if we could just do that (the logic went), they would know when to use the forecast, and all the parties would be happy. From the climate scientists' point of view, this was an amusing illustration of how the energy firms were unable to deal with probabilistic information.

In our conversations with various energy industry employees, we heard an interesting story (perhaps apocryphal, although it was not presented as such) along these lines. A California energy utility devised a new way of obtaining future supplies of energy that would result in lower energy costs to the consumers on average, but not necessarily every year. They applied to the California PUC to allow this method to be used in production, forthrightly disclosing how it was not guaranteed to reduce consumer costs every year, but it would do so over the long run. The PUC approved the application, and the firm implemented the scheme. For several years the scheme saved money compared to the previously used procurement scheme, and the firm passed the savings on to consumers. Then a year came when the new scheme resulted in increased procurement costs to the firm. When the firm tried to pass these increased costs on to the consumers, an objection was filed with the PUC, who subsequently disallowed the passing on of the increased costs, on the basis that the old, standard method would not have incurred the costs. Predictably, the result was that the firm abandoned the new method.

Perhaps the lesson learned here is that we found an intrinsic inertia resisting attempts to change business practices and start using climate forecasts in many of the energy businesses we tried to work with. It may be true that results can be shown to be better *on average, over time*, but that time might be decades, and the inevitability of a year or two worth of decisions worse than the "old" way of doing things was often considered too much of a disincentive to make the change viable.

7. Climate vs. Load Forecasts

From the point of view of climate scientists, forecasting electrical demand given a set of climate precursors is at least as easy, and likely more so, as the two step process of forecasting temperatures from the climate precursors and then forecasting demand from the temperatures. However, there are a number of practical difficulties in doing so.

First, the energy industry views energy demand and load forecasting methods as highly proprietary, and in our experience are not willing to share the data needed to make a statistical model of this kind except in unusual circumstances.

Also, the temperature/demand interface is viewed as a natural partition between "climate" skills and local "demand forecast" skills. We found that some of the more savvy industry people we worked with had broken down the final demand error into the weather component and the load component; i.e., when forecasting future energy demand, there will be some error arising from errors in the forecast of the weather at that future time, and errors that would be there even if the future weather were forecast perfectly. Depending on the quality of various load forecasting models, as well as the intrinsic predictability of weather in different regions, this might break out so that one-half to two-thirds of the final demand error was due to errors in the weather forecast, and the rest due to errors in the load forecast.

One of our experiences in Calenergy was illustrative of this issue. When we originally worked with the energy industry participant, they asked us to forecast the day irrigation pumps would turn on in central Idaho. We found a good relation between climate variables and the pump start day, but it had no predictive power since the climate variables needed to be measured in the same springtime month as the start day typically occurred. Upon further discussions, we discovered that the energy people wanted the pump start day predicted so that they could, in turn, predict *summer pump loads* from the pump turn-on date, a relationship they had previously discovered. It turned out to be straightforward to predict summer pump loads from the spring climate variables. So in this case it was *only* by going directly from climate to the electrical load that we were able to succeed.

8. Conclusions

Overall, the Calenergy project was a success, and resulted in scientific papers in the refereed literature as well as useful forecasts for our energy industry partners. However, this was not accomplished without some stumbles and mis-starts along the way. With the benefit of experience, the chances for success in such a project are likely to be maximized by doing the following.

It is imperative to have a specific, motivated, and technically savvy person in the energy firm to work with. The traditional paradigm of generating climate forecasts and presenting them to the energy industry participants, who will then receive the forecasts and incorporate them into their business decisions, did not work in any of the cases we worked on.

A problem must be found with a timescale that is both amenable to climate science and of interest to the energy industry. In practice we found this very difficult, and was one of the areas we were forced to compromise on in Calenergy. Three of the four cases we worked on concerned timescales of 5 days or shorter, and so were really more in the problem domain of weather forecasting than climate science.

Once a suitable problem is identified, the forecasted climate products need to be carefully considered. One the one hand, they might be a different set of products than the climate scientists expect. On the other hand, the final output climate forecast might be a type of information very different from what the energy industry participant expects.

Finally, consideration needs to be given to production issues and the different timescales over which climate research proceeds versus operational forecasts are generated. It should be understood up front who will generate the climate forecasts and for how long, and how extensively the forecasting will be supported. If businesses are going to be induced to change their practices based on a climate forecast, they want, reasonably enough, to be assured that the climate forecasts will be available in the future, and not simply as a one-off research product.